Information Sciences 289 (2014) 117–132

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Guidance compliance behaviors of drivers under different information release modes on VMS

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ARTICLE INFO

Article history:
Received 4 November 2011
Received in revised form 11 June 2014
Accepted 29 July 2014
Available online 19 August 2014

Keywords:
ITGS
Compliance behavior
Information release modes
SOAR
Multi-agent system

ABSTRACT

Driver's guidance compliance behavior, which is a crucial link in Intelligent Traffic Guidance Systems (ITGS), has a direct impact on guidance effect. Based on State, Operator, and Result (SOAR), which was a cognitive architecture, the traffic compliance agent was designed and elaborated in detail. In the paper, working memory (WM), long-term memory (LTM), operator selection, impasse solving, expected travel time determination, and chunking rule generation were described with the consideration of practical situations. Finally, two simulations with different information release modes were carried out under the same given condition, one was based on real-time flow statistics (M1), and the other was based on flow forecasting (M2). Through analyzing the changes of drivers' compliance rates and vehicles' lane-changing times under Variable Message Sign (VMS), M2 was proven to be more effective in alleviating traffic jam in the morning and evening peak periods and bring a higher compliance rate. This study laid a foundation for selecting the release modes of guidance information in both theory and practice.

1. Introduction

Among the various means and methods involved in Intelligent Transportation System (ITS), traffic guidance is one of the traffic management methods that can truly increase traffic performance and ensure traffic safety. Traffic guidance can help drivers make better decisions in travel choice and release their anxiety and stress during trips. The guidance compliance rate, which reflects driver's behavior toward traffic guidance information, should be taken into consideration in designing traffic guidance systems. In previous studies, drivers are generally assumed to make trips with 100% compliance rate, or a certain rate set by system [13,47,50,54]. In addition, these studies indicate that drivers regard expected utility as goals, who are allocated to the road network by using the user equilibrium approach [1,27,39]. However, these assumptions are not true in practice. Many other surveys have proven that the true compliance rate significantly deviates from the assumptions, and the conclusions challenge the conventional rate treatment process [1,27,39]. Many scholars have realized that the compliance rate of groups must be studied from the perspective of individual guidance compliance behaviors; hence, three primary methods have been developed in literature: survey [18,45], experiment [1,51], and simulation model [2,48].

Unlike traffic control signal, the guidance information released by Variable Message Sign (VMS) is just a kind of suggestion message, and it has no mandatory effect on drivers. So drivers can choose to comply with the VMS or not, which closely depends on their characteristics, their familiarity with road network, the content, the display form and release mode

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http://dx.doi.org/10.1016/j.ins.2014.07.045
0020-0255/

of information, their perception and comprehension of information, even their mood when they see VMS. And the dependencies vary gradually with driver's acceptation and adaption of VMS [3,7,10,26,28,29]. Among these factors, information release mode has a significant impact on drivers' guidance compliance behavior. The modes based on real-time statistic and traffic flow forecasting are the two most common ones. The aim of this research is to study the effects of the two information release modes on drivers' guidance compliance behaviors and find a better mode.

Compliance rate is used to represent drivers' degree of compliance with traffic information. The rate is the proportion of drivers who select the suggested roads of traffic information just because of the existing of information, and it reflects the effects of guidance information on drivers' compliance behavior. In this paper, the suggested path of information is the dynamic shortest path, i.e., the path costs the shortest time from current position to destination under the current traffic condition shown on VMS.

The remainder of the paper is organized as follows. Section 2 reviews the researches of drivers' guidance compliance behaviors. Section 3 introduces the State, Operator and Result (SOAR) architecture and analyzes its applicability. Section 4 describes the information release modes and SOAR based agent design of guidance compliance behaviors. Section 5 analyzes the simulation results and discusses the validities of simulation model and information release modes. Finally, the suggestions for practical use and future researches are given in conclusion.

2. Literature review

Bonsall et al. [8] investigated 100 drivers with vehicle-mounted guidance systems and found that 70% of them comply with the guidance system when they were familiar with the road network, while up to 90% when they were not. Cummings [12] surveyed 20 VMS systems in Europe and found that only 4–7% of the drivers obeyed the system in normal conditions, while 13% in special circumstances. Moreover, 5% of the drivers did not understand the VMS information and over 10% misunderstood it. Tarry et al. [46] monitored the VMS along the road network near Birmingham, UK, and found that 27–40% of the drivers obeyed the guidance when the VMS showed that an accident happened in front, but only 2–5% obeyed it when the VMS just notified the drivers of the traffic jams without reporting the cause [43]. Swann et al. [45] investigated the VMS near the estuary district in Forth of Scotland and found that 16% of the drivers diverted to the recommended path when the VMS showed traffic jams happened in front roads. Erke et al. [18] conducted a spot field investigation on two motorways and found that about 20% followed the recommendations of VMS, but 100% when the VMS showed that the road ahead was closed. Zhou et al. [58] analyzed 497 valid questionnaires about individual guidance compliance decisions in Beijing and found that the percentages of the drivers who *would change path*, *may change path*, *would not change path*, and *does not know what to do* were 16.9%, 65.4%, 11.5% and 6.2%, respectively. Chen [9] and Mo et al. [53] studied the parking guidance systems in Nanjing and Shanghai, and concluded that the behaviors of drivers in seeking guidance information as well as in understanding and complying with the information varied very much when the personal properties, travel characteristics, and the factors considered in selecting parking space were different among drivers. The abovementioned studies show the compliance rate is normally low. The main reasons are as follows: (1) there is no need for guidance information as drivers are already familiar with the roads; (2) drivers do not notice the information; (3) drivers do not understand the information; (4) drivers do not believe the information; (5) the information is received after drivers have already chosen a path, and (6) the readable distance of VMS is too short to read, leading to information missing [8,12,18,45,46].

The method based on experimentation is adopted to identify the laws of behavior and find the behavior influencing measures by analyzing drivers' responses to different experimental conditions. Allen et al. [4] allowed drivers to experiment with different origins and destinations (O–D) and different congestion degrees. Their results showed that drivers' compliance rate was high (beyond 70%) when they used route guidance mode. This experiment did not consider the recommended path would congest and then influence the guidance compliance behavior, which was actually very common in practice. Srinivasan et al. [44] adopted the Designer Workbench model of Corypheaus Corporation to create a software for developing experimental environments, in which different display approaches for guidance information were used to test their effectiveness based on the responses of 10 participants. They found that the approach with the highest compliance rate was the one using the countdown progress bar to show the distance between the current location and the front intersection. Chen et al. [11] allowed 99 participants to join a 20-day experiment on a road network simulated by a computer and found that the factors affecting drivers' guidance compliance behavior were the characteristics of guidance information (whether the information showed the recommended path, whether the road was connected or close to a highway, etc.), drivers' characteristics such as age, gender and education degree, and whether the information provided the reason for accidents or congestion. Wochinger et al. [51] found that drivers preferred different display modes and seemed to be more willing to comply with their favorite one. Adler [1] divided 80 participants into 4 groups with 2-factor measurement experiments. The measurements were repeated 15 times per person in one simulated road network. The results showed that the guidance compliance rates of drivers unfamiliar with the road network were higher than those familiar with it, it was because familiar ones derived little benefit from the provided information.

With the rapid development of computer technology, simulation models have been applied to study drivers' guidance compliance behaviors and has obtained certain results. For example, Lu et al. [37] proposed a complexity model of guidance compliance rate based on a traffic assignment Logit model to analyze the rate changing properties. Huang et al. [21] proposed a stochastic-user equilibrium model to study the changing processes of compliance rate in Advanced Traveler

Information System (ATIS). In recent years, researchers have paid more attention to multi-agent simulations to study drivers' guidance compliance behavior. Alder et al. [2] studied drivers' guidance compliance behavior from the perspective of cooperative games by simulating the interaction of various agents in the traffic system. Wahle et al. [48] proposed a two-layer agent framework: the first layer showed their perception and reaction to guidance information, and the second layer described their decision-making process. Dia et al. [15] added drivers' beliefs, capacities and various behavior rules into agents when they studied drivers' reactions to different traffic information. They also proposed an agent framework with cognitive function and then studied the changing processes of guidance compliance behaviors.

3. SOAR cognitive architecture

As a general intelligent architecture, SOAR was developed by Laird et al. in 1987 [30]. It is a cognitive architecture with a wide range of applications, and it is mainly used to investigate about knowledge, thinking, intelligence, and memory. In SOAR, a state is a representation of the current problem-solving situation, an operator transforms a state and produces a new state, and a goal is a desired outcome of the problem-solving activity. As SOAR runs, it is continually trying to apply the current operator and select the next operator (a state can have only a single operator at a time) until the goal is achieved.

SOAR architecture primarily includes the perception and action interface, long-term memory (LTM), working memory (WM), and some underlying mechanisms, such as decision procedure, learning process, etc. As shown in Fig. 1[38], the environment is mapped into WM through perception, and the inner representations are returned to the outside through the action interface. WM describes the current problem solving situations, and LTM stores long-term knowledge containing procedural memory, semantic memory, and episodic memory. SOAR accomplishes the processes of choosing and applying operators through a fixed decision-making cycle. With the decision cycle, SOAR has four different types of learning mechanisms: reinforcement learning, chunking, episode learning, and semantic learning [42].

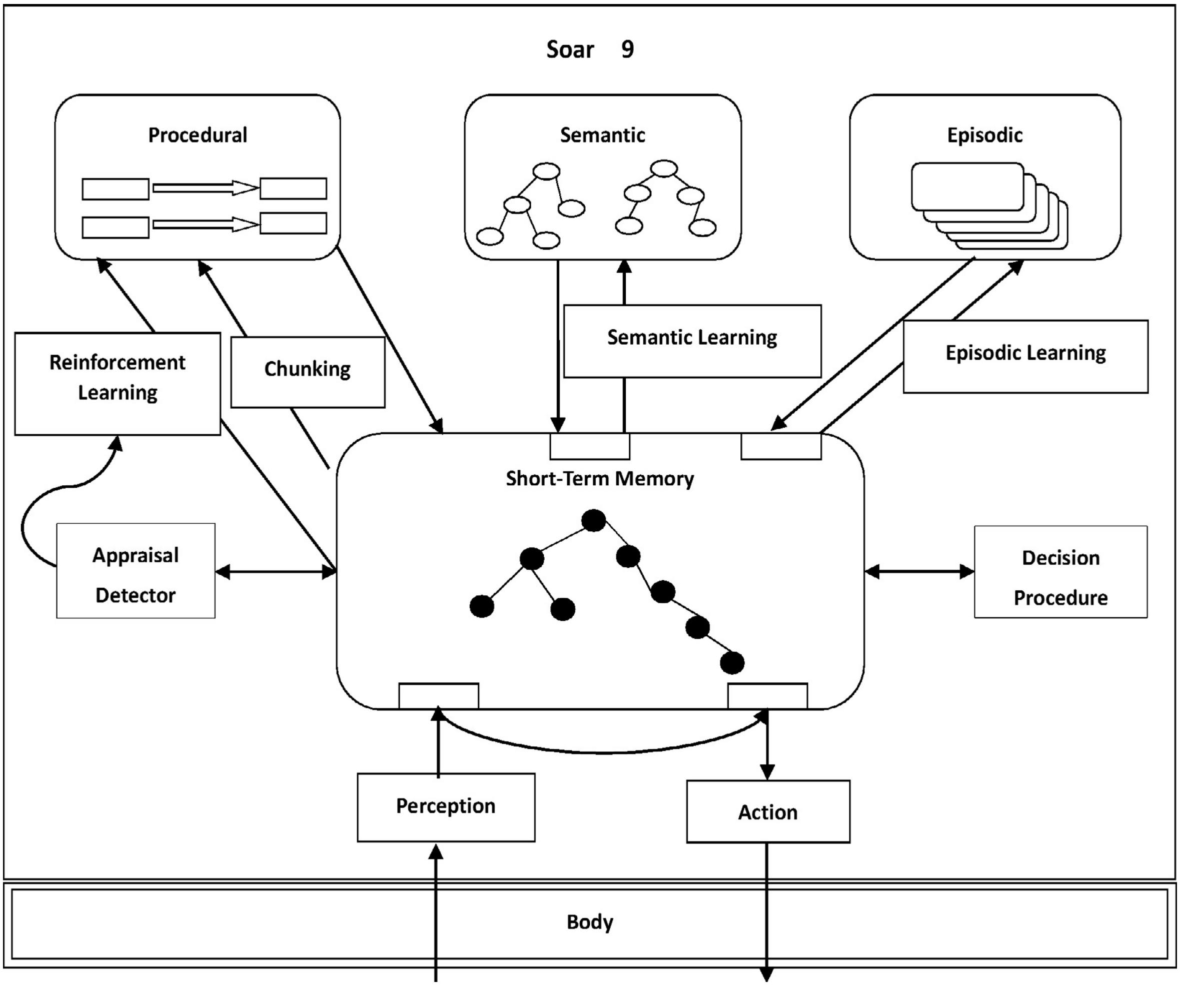

Fig. 1. SOAR architecture.

The most important algorithm of SOAR is to determine the preferred operator as only one operator can be selected for a state at a given time. First, trigger all operators which are labeled acceptable; second, discard all acceptable operators that are also labeled rejected; third, determine the dominance relations among the remaining operators with specific rules; then, discard all dominated operators; and last, select the operator when there is only one, or generate an impasse followed by learning to solve it when zero or more than one operator remains. Detailed illustrations of developed SOAR algorithms related to guidance compliance behavior decision are presented in 4.4.3 and 4.4.4.

Cognitive science is developed to study human perception and information processing process, and it provides significant methods to further study the human cognitive mechanisms. SOAR, one of the most popular cognitive architectures, has been applied successfully to simulate many aspects of the human behaviors [24,38]. Multi-agent System (MAS), which breaks down the problems into many agents, is a branch of distributed artificial intelligence. MAS is suitable for solving this kind of problems if the problem domain is distributed geographically and the sub systems exist in a dynamic environment with flexible interaction. The management of traffic guidance systems fully meet these conditions. Thus, an agent model based on SOAR is developed to study drivers' guidance compliance behaviors under two information release modes, which are based on real-time statistic and traffic flow forecasting, respectively.

4. Method

4.1. Research object

Fig. 2 [57] is a graphic VMS [20]. It is near the east gate of Renmin University of China, and about 300 meters from SITONG Bridge along southbound direction. Red, yellow and green shown on the VMS indicated that the road is very congested, generally crowded and smooth, respectively. The traffic conditions shown on VMS are updated every 5 min. The sections, between JIMEN Bridge and XIZHIMEN Bridge and between SUZHOU Bridge and ZIZHU Bridge, are both expressways. That means there are no signalized intersections in these two sections. Whereas, there are 4 signalized intersections in which different levels of control delays exist between SITONG Bridge and BAISHIXIN Bridge. Fig. 3 shows the guidance area related to this VMS, and the roads marked with green are shown on VMS. The reason for choosing this VMS to study, for one thing, is the suitable distance between the VMS and SITONG Bridge, the travel time from VMS to downstream road is not too long or too short, the real-time performance of VMS is not affected, and also drivers have enough time to switch after passing the VMS; for another thing, is the slight differences among the travel times of different paths shown on VMS when the road is smooth, the ambilateral paths are mainly comprised of expressways with design speed being 80 km/h, the middle paths are comprised of truck roads with design speed being 60 km/h, but the length of ambilateral paths are generally longer than the middle paths. So the effect of VMS on drivers' route choices behavior and drivers' routing preference are more obvious.

4.2. The release modes of guidance information shown on VMS

Whether or not drivers will comply with the guidance has a close relationship with the accuracy of the guidance information. The information not only reflects the current condition or forecasts the road condition precisely, but also considers drivers' trip expectation. When the congestion level represented by information varies greatly from drivers' perception of the true congestion level after following the recommendation, drivers will begin to doubt the information accuracy, which affects their subsequent behavior. Nevertheless, a certain contradiction between optimums of individual and group does exist in selecting the optimal route. For example, if the roads on the left, forward, and right are represented by yellow, yellow and green, respectively, many drivers maybe turn to the right, then the right road is probably going to be the most

Fig. 2. Graphic VMS.

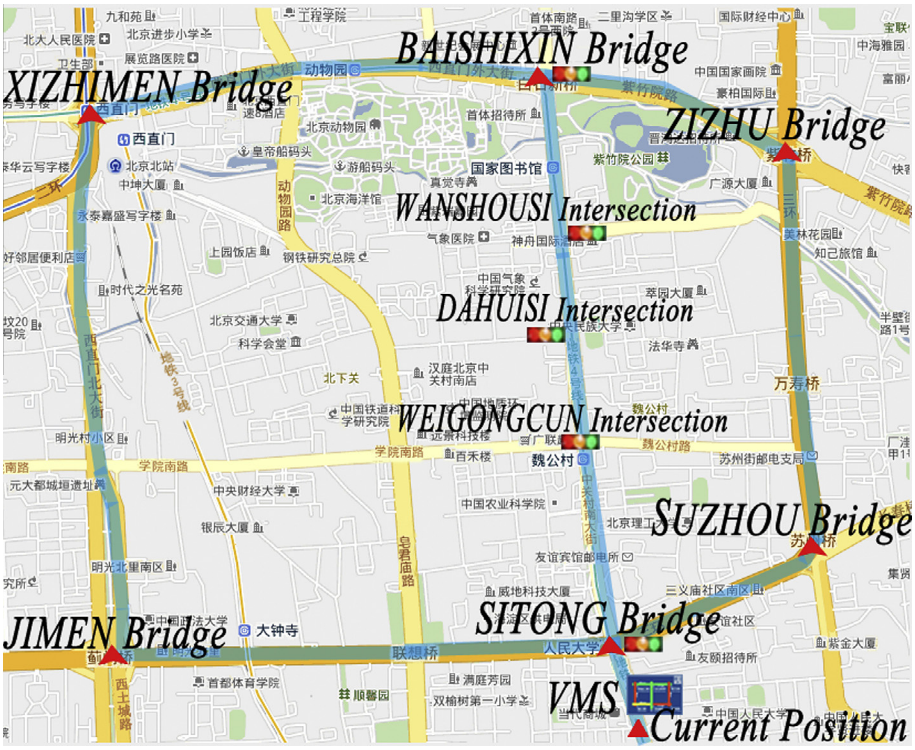

Fig. 3. Road network.

time-consuming because of the large influx of drivers. Therefore, the information accuracy and the compliance rates of different driver groups at different time should be considered in selecting the information release mode. This paper discusses the following two information release modes.

- M1 is based on real-time statistic: VMS information, which is updated every 5 min, represents the almost real-time traffic conditions. At present, M1 is adopted in practice.
- M2 is based on traffic flow forecasting: VMS information considers the inflow capacity of the next guidance cycle. Road comprehensive saturation is adopted to represent traffic flow. The information contains the traffic flow of current time and the inflow from the upstream road in the next guidance cycle. M2 is a computational method based on traffic flow forecasting with guidance information [56]. Currently, a science and technology program of Beijing named Road Traffic Flow Simulation and Forecast System is in process.

4.3. Questionnaire survey

Scene simulations in the questionnaire are conducted to ascertain the SOAR agent parameters. Questionnaires are sent in two continuous surveys. The first one is route choice survey under different VMS information. Besides route choice simulations, drivers' socio-economic characteristics and travel characteristics are also obtained. The second one is decision rule survey. According to the data analysis of the route choice behavior, part of the respondents is selected to investigate the long-term memory and learning rules in the second survey.

According to field observation, 12 kinds of typical VMS information are chosen in the route choice simulation part of the first questionnaire. The 12 scenes (Fig. 4) are refined from some specific time periods including the morning peak, evening peak and normal time periods. Fig. 4a is a control group which indicates that all roads are smooth, and Fig. 4b–l are experimental groups. Drivers choose route based on experience under Fig. 4a, and based on experience and information under Fig. 4b–l.

According to the simulation scenes, 84 combinations of decision conditions are provided, and drivers are required to select their actions and preferences to generate decision rules in the second survey. The specific descriptions of rule generation and data processing are in 4.4.2.

The first survey began in April 2011, we investigated the masses around the vicinity of the VMS, including the subway stations, huge shopping malls, schools and hospitals, where many people gathered together. We recorded the phone numbers and email addresses of people who were willing to participate in. Then the questionnaires were sent out to the

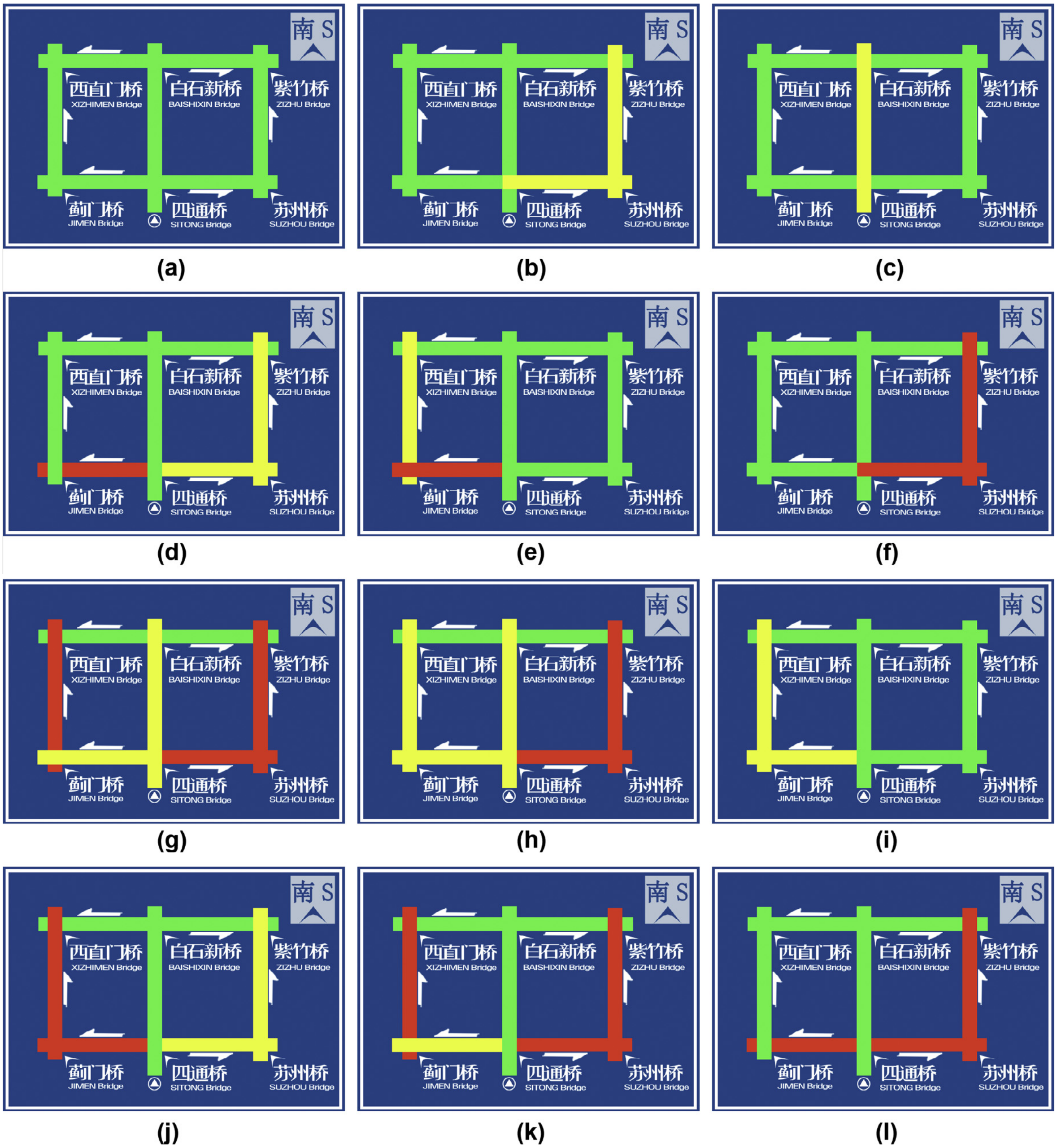

Fig. 4. Scenes 1–12.

participants and retrieved through internet. Totally, 423 questionnaires were sent out and 328 questionnaires were retrieved in the first survey, recovery rate reached 77.5%. The number of route choice of drivers simulated in different guidance scenes were 7872. After the data analysis of first survey, 123 respondents from the participants received questionnaire in the second one, and 105 questionnaires were sent back, recovery rate reached 82.0%, 8820 production rules were simulated totally. Each respondent was paid a 30 yuan mobile phone recharge card.

4.4. Agent design of traffic guidance compliance behavior

4.4.1. Working memory

In SOAR, the current situation, including the data from sensors, results of intermediate inferences, hierarchy states, active goals and active operators, is held in the WM. The reasoning and decision-making processes of agents with dynamic

Table 1
Attributive classification of drivers.

Drivers category	Age	Monthly income	Route choice style	Sample size
1	[18, 30]	[5000, 10,000]	Experience and information type	43
2	[31, 40]	>10,000	Experience and information type	39
3	[31, 40]	[5000, 10,000]	Experience and information type	33
4	[31, 40]	[5000, 10,000]	Fixation type	29
5	[18, 30]	<5000	Experience and information type	27
6	[18, 30]	<5000	Fixation type	22
7	[18, 30]	[5000, 10,000]	Fixation type	22
8	[18, 30]	[5000, 10,000]	Experience type	22

information about the world and internal reasoning are conducted in WM. The WM compositions of different driver groups are distinct, which depends mainly on the influences of various factors on drivers' decision-making behavior. In this paper, the following factors are extracted as drivers' attributes, including gender, age, driving years, average annual mileage, personal monthly income, education level, driving style, occupation, car type, driving goal, trust degree in VMS, the familiarity with road network and route choice style. With the above factors as independent variables, compliance rate as the dependent variable, ordinal regression is used to analyze the correlation between the compliance rate and the factors. Wald test finds three variables are significant among all their value ranges at 0.05 significant level. Drivers are classified by these three variables, including age, monthly income and route choice style, and the most typical 8 types of drivers are shown in Table 1. The sample size of each category is more than 20, the 8 categories account for 72.3% of the total. In the first survey, the external influencing factors and the probable actions are investigated, which are regarded as the input and output (operator) of WM respectively (Table 2). The attributes affecting drivers' guidance compliance behavior the most are as follows: queue lengths of left-turn and straight-forward paths (short, medium and long), signal information of left-turn and straight-forward directions (red and green), VMS information (the average congestion degrees of left-turn, straight-forward and right-turn paths), traffic condition of the current road (very congested, generally crowded and smooth), the predictive traffic conditions of downstream roads (the congestion degrees of left-turn, straight-forward and right-turn paths, which are predicted by drivers), drivers' current mood (relaxed or impatient), the destination (area 1, 2, or 3) and route choice style (fixation type, experience type, experience and information type, and guidance information type). The output attributes include choosing the downstream paths from left-turn, straight-forward and right-turn paths, changing the predictive traffic conditions of three downstream paths, changing destination, changing route choice style, and changing the mood. The details of the output are generated from the second survey.

4.4.2. Long-term memory

Long-term memory is the area where achievements are stored. Procedural memory is primarily responsible for controlling behavior. It maps to operator knowledge directly. Semantic and episodic memory usually come into play only when procedural knowledge is in some way incomplete or inadequate for the current situation. Semantic memory is not involved here. The procedural knowledge is represented as English-like *if–then* rules representing associations between a set of conditions (i.e., the "*if*" part of the rule) and a set of actions (i.e., the "*then*" part of the rule). First, the "*if*" part tests the perception and elements of the state. If there is a match between the "*if*" part and the elements in WM, we say that the rule has

Table 2
The input and output of working memory.

No.	Attributes (remark)	Input\output	Value (code)
1	Queue waiting time of left-turn and straight-forward lanes (no queues in the right-turn lane)	Input	Short/medium/long (1/2/3)
2	Signal light of left-turn and straight-forward lanes (no signal light for turning right)	Input	Red/green (R/G)
3	VMS information about left-turn, straight-forward and right-turn paths	Input	Green (smooth)/yellow (generally crowded)/red (very congested) (R/Y/G)
4	Traffic condition of current road	Input	Smooth/generally crowded/very congested (1/2/3)
5	Predicted traffic condition of left-turn, straight-forward and right-turn downstream roads	Input	Smooth/generally crowded/very congested (1/2/3)
6	Current mood	Input	Relaxed/impatient (0/1)
7	Destination	Input	Left area/forward area/right area (1/2/3)
8	Route choice style	Input	Fixation type/experience type/experience and information type/ guidance information type (1/2/3/4)
9	Change the predicted conditions of downstream roads	Output	Generate based on questionnaire options and their preferences
10	Change mood	Output	Generate based on questionnaire options and their preferences
11	Change destination	Output	Generate based on questionnaire options and their preferences
12	Change route choice style	Output	Generate based on questionnaire options and their preferences
13	Choose the downstream paths	Output	Generate based on questionnaire options and their preferences

Table 3
Selected initial rules of an agent category.

Number	Conditions	Action	Preference
r1	S-D(3) *and* V-S(RRG) *and* C-S(RR) *and* P-D(331) *and* Des(2)	Loc(3)	4
r2	S-D(3) *and* V-S(RRG) *and* C-S(RR) *and* P-D(331)	P-D(311)	3
r3	S-D(3)*and* V-S(RRG) *and* C-S(RR) *and* Des(1) *and* R-C-S(1)	R-C-S(4)	2
r4	S-D(3) *and* V-S(RRG) *and* C-S(RR) *and* P-D(311) *and* Que(31)	Loc(2)	2
r5	V-S(RRG) *and* C-S(RR) *and* Des(3)	Loc(3)	5
r6	V-S(GRR) *and* Que(13) *and* Des(2) *and* Mo(1)	Des(1)	2

Note: S-D, V-S, C-S, P-D, R-C-S, Que, Des, Loc and Mo are short for Sense-Density, VMS-Sign, Control-Sign, Predict-Density, Route-Choice-Style, Queue, Destination, Location and Mood, respectively.

been triggered. This, in turn, causes the "*then*" part to fire by either sending a message to the motor system or suggesting changes to the goal, state, and operator. Thus, any rule that matches the elements will change them.

The initial rules are generated from the second survey by excel VBA program. The scenes contained in the survey are the descriptions of combinations of input attributes in WM. The combinations of input attributes are chosen based on the analysis of recovery questionnaires in the first survey. Given certain scenes, respondents were required to choose the corresponding output attributes (e.g., choosing the downstream path, changing destination and changing route choice style) and their preferences to perform the output (the willingness gets stronger and stronger from 1 to 5). Through the statistical analysis of survey data, the behavior preferences of different driver categories in various scenes are calculated. Input attributes, output behaviors and preferences compose a number of rules. These rules are the initial rules in LTM. The number of average initial rules of each agent category is 214. Selected initial rules of a driver agent are shown in Table 3.

Taking r6 as an example, if the VMS shows the left-turn path is smooth, and the right-turn and straight-forward paths are very congested, the queuing length of left direction is short, but which of straight direction is long, the driver' destination is area 2, and he is impatient, then he may change his destination to area 1 with the preference being 2. Rules are to be deleted or added dynamically in the learning process by learning mechanism.

The episode knowledge consists of the specific experiences and memories that serve as sources of episodic learning. Once a route choice decision is finished, SOAR records the current decision, the corresponding state transition path (i.e., recording the process from the initial state to the final state by applying operators) and the feedback preference in preparation for the next impasse.

4.4.3. Procedural operator selection

After firing the procedural rules, the operators are proposed to compare and select. Preference is used for the comparison and selection of the candidate operators. Each rule consists of conditions to be matched, the operator to be proposed when the conditions are matched, and the numeric preference of the proposed operator.

In this research, numeric preference is evaluated to select the proposed operator. If the preferences are sufficient to select one operator, a single operator is chosen into WM and to be applied to change the state, or if the preferences are incomplete or contradictory among all the proposed operators (e.g., there are more than one operator having the highest preference), an impasse occurs and a sub-state is created to resolve the impasse. According to the external feedback after applying each operator, the preference changes closer to reality and provides the drivers more accurate information to aid them in making a decision. The detailed selection process of proposed operators is described below.

(1) $O(s)$ is the set of candidate operator set in state s. If the size $|O(s)|$ is equal to 1, the only operator $o \in O(s)$ is chosen into WM, otherwise, continue to step 2.
(2) If $|O(s)| > 1$, $p[o_{\max}(s)] - p[o_{\sec}(s)] \geqslant \tau(s,k)$, then an operator $o \in O(s)$ is chosen into WM with roulette mechanism; otherwise, continue to step 3. $p[o_{\max}(s)]$ and $p[o_{\sec}(s)]$ are the preferences of the best and the second-best operators, and $\tau(s,k)$ is the threshold when the kth type of drivers selects operator directly in state s.
(3) If $O(s_i) = \emptyset$ or $|O(s)| > 1$, $p[o_{\max}(s)] - p[o_{\sec}(s)] < \tau(s,k)$, then no operator can be chosen directly, an impasse occurs and chunking begins, which is introduced in Section 4.4.4.
$\tau(s,k)$ is calibrated as follows. Among the initial rules of the kth type of drivers, $\bar{\tau}_{\max}(s,k)$ is the average preference of rules which are believed to occur by 90% of the drivers in state s, while $\bar{\tau}_{\min}(s,k)$ is the average preference of rules which are believed not to occur by 90% of the drivers, and $\tau(s,k) = \bar{\tau}_{\max}(s,k) - \bar{\tau}_{\min}(s,k)$. That is to say, $\tau(s,k)$ is calibrated approximately at a 90% confidence level.

4.4.4. Learning mechanism

Chunking, the main learning method of guidance compliance agent, happens to solve an impasse and create chunking rules from sub-states. Chunking begins when the operator set is null or the difference between the candidate operators is smaller than the threshold of selecting operator. Then, the existing production rules and the episodic memories related to the expected result are searched automatically in order to create chunking rule. If there are no cues relating to current state, then the match accuracy decreases, i.e., the conditions of matching operators are not that strict. Match accuracy is the

proportion of the conditions being matched to the state elements. When the accuracy is satisfied, the operators in actions are proposed. For example, if one rule has 6 conditions, and only 5 conditions are satisfied in one state, then the operator in the rule will be proposed when the match accuracy is decreased to 0.8. Subsequently, the newly matched operators from loose conditions are applied to move to the goal state. Finally, the operator is added into the state in which the impasse is resolved, and chunking rule is generated. The detailed process is described below.

(1) The current state s_i is transformed from the initial state s_0 through i state transitions. If $O(s_i) = \emptyset$ or $|O(s_i)| > 1$, $p[o_{\max}(s_i)] - p[o_{\sec}(s_i)] < \tau(s,k)$, then chunking begins, let $j = i + 1$, and continue to step 2; otherwise, the procedural rule is used to select an operator as depicted in Section 4.4.3.
(2) If $j = 0$, turn to step 5; otherwise, $j := j - 1$ and continue to step 3.
(3) The set of operators which are involved in all the state transition paths containing the state s_j in the episodic memory, is recorded as $O_q(s_j)$. If $O_q(s_j) = \emptyset$, then turn to step 2; otherwise continue to step 4.
(4) The operator $o \in O_q(s_j)$ which has the highest feedback preference in the episodic memory, is chosen into WM to solve the current impasse, and continue to step 7.
(5) If $O(s_i) = \emptyset$, then decrease the match accuracy by a step size of 0.1 until $O(s_i')$ comes, and continue to step 6. That means, the conditions of rules are matched in a discrete decreased proportion in order to propose operators. s_i' is the new state after the match accuracy changes.
(6) An operator from $O(s_i)$ or $O(s_i')$ is chosen into WM with the roulette mechanism to solve the impasse, and continue to step 7.
(7) The end.

Chunking rules are added into LTM with a probability, which is closely related to the expected utility of applying the chunking operator. Assuming drivers' perception errors follow the independent and identical Gumbel distributions, a logit formula is adopted to calculate the probability, $P[r(l)] = \frac{1}{1+\sum_{j\neq l}\exp[(U_j - U_l)]}$, where, $P[r(l)]$ is the probability of the rule in which path l is chosen entering into LTM, U_j is the utility of applying the rule in which path j is chosen.

The utility is mainly influenced by the expected travel time. The transformation from time to utility is based on cumulative prospect theory, travel time is regarded as gain or loss to calculate the prospect value, which is described in detail in [52]. Hence, the expected travel time on each path is estimated based on a convex combination of experience and information proposed by Ben-Akiva et al. [5]. The expected travel time on $t + 1$ times is given by $T_u(t + 1) = \alpha T_i(t + 1) + (1 - \alpha)T_e(t)$, $0 \leqslant \alpha \leqslant 1$, where $T_i(t + 1)$ and $T_e(t)$ are the suggested travel time by VMS on $t + 1$ times and the experiential travel time on t times, respectively. α is the weight of guidance information in the travel time updating process. For example, a high value of α ($\alpha > 0.5$) suggests that drivers give more importance to guidance information and less to the experiential perception. Thus, α is also regarded as drivers' average trust degree in VMS information, which is investigated from the first survey, in which drivers are required to judge their own trust degree in VMS.

4.5. Simulation conditions

The surveys are taken based on the area shown in Fig. 2, the key nodes and destination areas are shown in Fig. 5. To facilitate the description, the road network is simplified as Fig. 6, where nodes 2, 3, 4 and 5 represent SITONG Bridge, XIZHIMEN Bridge, ZIZHU Bridge and BAISHIXIN Bridge, and the other nodes are entrances and exits of simulation road network. The

Fig. 5. Simulation road network.

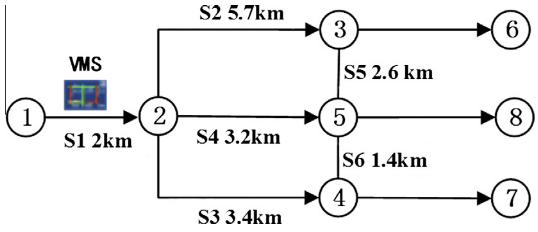

Fig. 6. Simplified road network for simulation area.

Table 4
Lengths of road sections.

Road section		Length (km)
Origin	Destination	
SITONG Bridge	SUZHOU Bridge	1.2
SITONG Bridge	BAISHIXIN Bridge	3.2
SITONG Bridge	JIMEN Bridge	2.7
SUZHOU Bridge	ZIZHU Bridge	2.2
ZIZHU Bridge	BAISHIXIN Bridge	1.4
BAISHIXIN Bridge	XIZHIMEN Bridge	2.6
XIZHIMEN Bridge	JIMEN Bridge	3.0

Table 5
Average car speeds corresponding to different colors shown on VMS.

Color	Red	Yellow	Green
Car speed (km/h)	7.45	17.72	29.26

Table 6
Intersection delays.

Intersections	SITONG Bridge	WEIGONGCUN intersection	DAHUISI intersection	WANSHOUSI intersection	BAISHIXIN Bridge
Left direction					
Stopped delay(s)	22.5	35.36	32.14	25.71	30.53
Driving delay(s)	13	5	4	8	0
Total delay(s)	35.5	40.36	36.14	33.71	30.53
Forward direction					
Stopped delay(s)	19.29	28.93	33.51	26.8	32.79
Driving delay(s)	5.1	5	3.5	4.5	0
Total delay(s)	24.39	33.93	37.01	31.3	32.79
Right direction					
Stopped delay(s)	0	0	/	0	0
Driving delay(s)	0	3	/	4.36	0
Total delay(s)	0	3	/	4.36	0

main traffic data, including the road lengths, average speeds corresponding to different road condition and control delays of different directions, are shown in Tables 4–6. All the data are collected from traffic spot investigation. The simulation road network and traffic environment are set based on these actual data. In order to verify the generalization performance of the simulation, the sensitivity analysis of the driver composition and road condition probabilities are conducted, we find the simulation results are basically identical when the changes are not too large. Hence, only the simulation results and analysis based on the actual traffic data are presented.

The simulation experiment is conducted with the microscopic simulation platform which is developed based on the cellular automaton theory [6,19,31,43,55]. The length of the cell is 7.5 meters. The simulation is carried out under M1 and M2, respectively.

Each experiment is conducted from 6 am to 10 pm for 10 continuous days, i.e., 160 h. To simulate the repeated compliance behavior, the vehicles are required to queue to $s1$ from *Intersection 1* after they exit from *Intersection 6, 7 or 8* to match the departure frequencies, which change dynamically based on the practical data during peak and off-peak hours.

Table 7
The comparison between the compliance rates in questionnaire and simulation experiment of different destination areas.

Scene number	V-S	Compliance rate in simulation experiment (%, corresponding destination area is 1/2/3)	Compliance rate in questionnaire (%, corresponding destination area is 1/2/3)	Simulation times in questionnaire
Scene 2	GGY	41.0/29.2/26.5	36.6/26.5/30.4	492
Scene 3	GYG	37.1/42.8/66.9	32.3/45.8/62.5	492
Scene 4	YGY	33.4/44.3/23.4	34.0/38.6/25.0	492
Scene 5	RGG	21.6/20.1/14.2	22.1/17.7/14.3	492
Scene 6	GGR	39.5/30.8/24.4	46.0/31.3/21.4	492
Scene 7	RYR	34.3/24.3/24.3	40.0/22.5/21.4	492
Scene 8	YYR	21.3/8.5/14.9	18.7/8.0/14.3	492
Scene 9	YGG	15.9/11.2/6.7	17.9/10.4/7.1	492
Scene 10	RGY	46/27.0/19.3	46.8/26.5/19.6	492
Scene 11	RGR	49.2/30.7/19.7	49.4/36.0/17.9	492
Scene 12	YGR	32/29.9/7.8	34.9/31.3/8.9	492

Table 8
The comparison between compliance rates in questionnaire and simulation experiment of different driver categories.

Drivers category	Compliance rate in questionnaire (%)	Sample size	Compliance rate in simulation (%)	The number of agent in simulation
1	32.3	43	33.8	135
2	44.4	39	44.8	91
3	34.7	33	32.8	78
4	27.7	29	26.3	71
5	28.3	27	28.7	64
6	17.0	22	15.7	57
7	27.9	22	29.3	54
8	21.4	22	23.1	68

5. Results and discussion

5.1. Validity analysis of the model

If an agent gets its final state just by one state transition, then direct mapping between the inputs and the selection of the downstream path is formed. The convergent mapping relations in the simulation are extracted to analyze the validity of the model through the comparison among the convergent mappings, scene conditions and route choice decisions in the questionnaire. The convergent mapping relation is comprised by a state and the downstream path choice. Table 7 shows the comparisons between the compliance rate from simulation after convergence and the rate deduced from questionnaire corresponding to specific destination areas under different scenes, and Table 8 with different categories of drivers. Time varying characteristics of guidance compliance rates of different driver categories are also concluded in Fig. 7.

Table 7 shows scene 3 with the destination area being 3 has the highest compliance rate. Its compliance rates in questionnaire and simulation experiment are 62.5% and 66.9%, respectively, which are more than 2 times of the average compliance rates being 27.8% and 27.7%. This is because the spatial distances of right-turning and straight-forward paths are similar for area 3, but right-turning path is expressway which has no control delay, and straight-forward path has three signalized intersections which have large control delays, also the VMS shows right-turning path is smooth and straight-forward path is generally crowded. Scene 9 with the destination area being 3 has the lowest compliance rate. Its compliance rates in questionnaire and simulation experiment are 7.1% and 6.7%. This is because the main paths are straight-forward and right-turning paths for area 3, and VMS shows the both paths are smooth, so most people choose route according to their fixed habits, and the proportion to change route choice habit is very small. The maximum deviation between the compliance rates in questionnaire and simulation experiment is 14.76%, which exists in scene 4 for destination area 2. Left-turning, straight-forward and right-turning paths are all optional for area 2, and the difference of the travel time among the three paths is very small. In this circumstance, the initial rules generated from questionnaire will occur with errors, and results in a large deviation between simulation experiment and questionnaire.

The compliance rates of previous researches were very distinct. There were rarely more than 40% for VMS, the compliance rates to different VMSs were about 4–7%, 16%, 5–25%, 30%, 27–40% and 6–41% [12,14,45,34,40,46]. For vehicle navigation system mounted in car, the compliance rates were higher, which were more than 70% [4,8]. In our study, the compliance rates are within the range of 6.7 to 66.9% and the average compliance rate is 27.8%, which fall within the scope of previous studies.

The combination of 3 destination areas and 11 kinds of VMS information leads to 33 guidance scenes. The mean error of compliance rates between questionnaire and simulation is 8.24%, the maximum error is 14.76% and the minimum error is 0.40%. On the whole, the deviation between the compliance rates in questionnaire and simulation is small, which shows that using SOAR agent to describe drivers' guidance compliance behavior is effective for all the typical scenes.

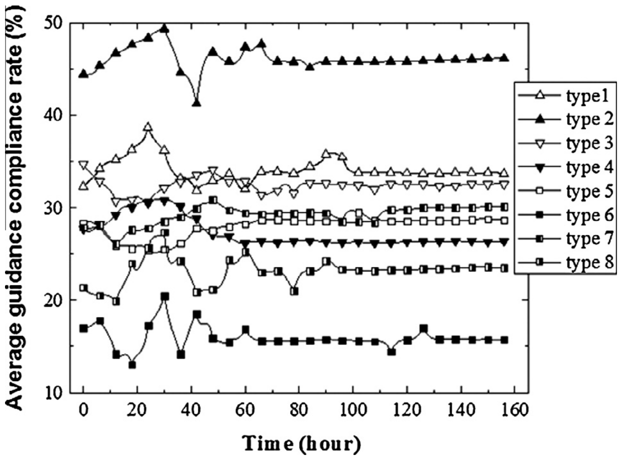

Fig. 7. Time varying characteristics of compliance rates.

Table 8 shows the highest compliance rate is 44.8%, which belongs to drivers with age being 31 to 40, monthly income being more than 10,000, and route choice style being experience and information type. This kind of driver has the highest monthly income among the 8 kinds of drivers. Time is more valuable to them, so they depend more on guidance information, thus their average compliance rate is the highest. The lowest rate is 17.0%, which belongs to drivers with age being 18 to 30, monthly income being less than 5000, and the route choice style is fixation type. Their low compliance rate is due to their low time value, they incline to choose fixed path. In addition, these drivers have shorter driving years as they are younger, they lack experience in driving, so they are reluctant to choose unfamiliar paths, and the possibility of changing path under VMS is also small. Among the 8 kinds of drivers, the mean deviation of their compliance rates between questionnaire and simulation experiment is 4.76%, and the maximum deviation is 7.94%. The above data and analysis show that using SOAR agent can accurately describe different kinds of drivers' decision making processes in guidance compliance behavior.

Fig. 7 shows the time varying characteristics of compliance rates of different driver categories. The starting points of curves fall near the compliance rates in the questionnaire, which shows the compliance rates generated from simulation in general accord with the rates in the questionnaire. Thus, the initialized rules of SOAR agent comparatively accurately reflect drivers' decision making process in route choice behavior. In the beginning of simulation, the compliance rates change greatly. As the simulation goes on, the fluctuations of compliance rates are gradually stable, and basically reach convergence after 130 h from the beginning of simulation. This is because rules are insufficient in supporting decision making in the beginning, chunking and feedback learning are needed to product new rules and gradually perfect the long-term memory, and mappings from initial conditions to route choice decisions are converged in typical scenes finally. It is a process of continuous exploration, feedback and learning. After the convergence in the simulation experiment, the compliance rates are basically similar with the rates in the questionnaire, which shows the decision mechanism of SOAR agent can basically reflect drivers' actual route choice decision processes.

5.2. Validity analysis of M1 and M2

Fig. 8 shows the average compliance rates of 8 driver categories under M1 and M2 after the simulation converges. It is obvious that M2 has a greater influence on drivers than M1 for all driver categories. The detailed average compliance rates and the differences between M1 and M2 are shown in Table 9.

As shown in Table 9, the average compliance rate of all driver under M2 is 9.36% higher than that under M1, i.e., the guidance information under M2 has a greater influence on drivers. SOAR agent recognizes that M2 is better able to improve travel efficiency in the continuous processes of decision, learning and feedback. The proportion of drivers choosing to obey the guidance information under M2 is larger than that under M1. The guidance compliance rates of the 4th, 6th and 7th driver categories under M2 are just a bit higher than the ones under M1, the average of increments is 4.50%, while the average compliance rate of other categories under M2 is 12.28% higher than the one under M1. It is found that the common feature of the 4th, 6th and 7th categories is their fixation route choice style, which indicates that they depend less on VMS information, and are also less likely to change their fixed habits even when the accuracy of guidance information is improved.

Road s1 is divided equally into 10 consecutive intervals named from I1 to I10 along the direction of traffic flow. In order to reflect the queuing characteristics under different guidance modes, average vehicle numbers of different time moments in I9 and I10 are calculated in Fig. 9.

Fig. 9a shows the average vehicle numbers of I10 in different time moments under M1 and M2. The mean difference between these two modes is 5.30% and the biggest difference is just 10.5%, which confirm that the congestion degrees of the area within 200 meters from the intersection under M1 and M2 are similar. The advantage of M2 is shown in Fig. 9b,

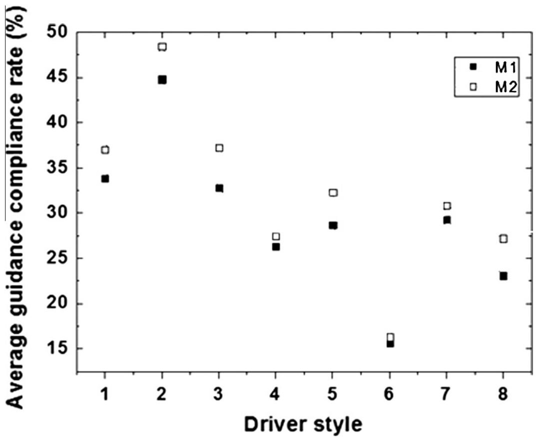

Fig. 8. Average guidance compliance rates of different drivers.

Table 9
The comparison of average guidance compliance rates between M1 and M2.

Driver categories	Rates under M1 (%)	Rates under M2 (%)	Absolute differences (%)	Relative differences (%)
C1	33.8	36.8	3	8.88
C2	44.2	48.4	4.2	9.50
C3	32.6	37.2	4.6	14.11
C4	26.5	27.7	1.2	4.53
C5	29.5	33.3	3.8	12.88
C6	16.4	16.8	0.4	2.44
C7	29.4	31.3	1.9	6.46
C8	24	27.9	3.9	16.25
Avg.	29.6	32.4	2.9	9.36

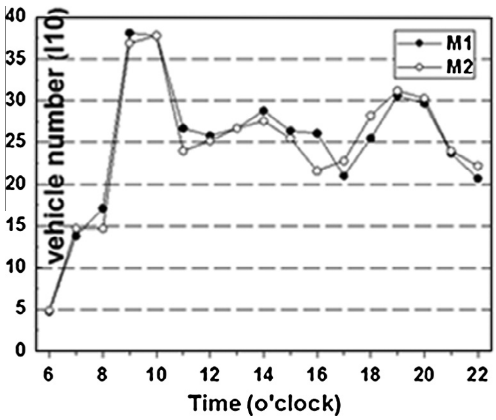

Fig. 9a. Average vehicle number of I10 under M1 and M2.

the average vehicle numbers of I9 in different time moments under M2 are all smaller than the numbers under M1, and the average reduction proportion is 14.08%. The advantage of M2 on dredging traffic flow is more obvious in the morning and evening peak periods. Compared with M1, the average vehicle number of I9 at 8 o'clock is 31.63% less, which indicates that M2 has a better effect on alleviating traffic congestion in the range of 200 to 400 meters from the intersection.

The number of vehicle changing lanes after it enters into the area influenced by VMS is an important indicator that represents drivers' guidance compliance behavior. It is a specific performance of drivers' compliance behavior toward guidance information. The more the lane-changing times are, the more greatly the information influences on drivers, and vice versa. Fig. 10 shows the statistical spatial–temporal-density diagram of lane-changing times of vehicles on s1 under M1 and M2. The spatial–temporal plane is divided into grids of time length 20 h and space length 105 m (i.e., s1 is divided into 19 cells). The sum of the lane-changing times in a grid divided by the size of a spatial–temporal plane equals the density.

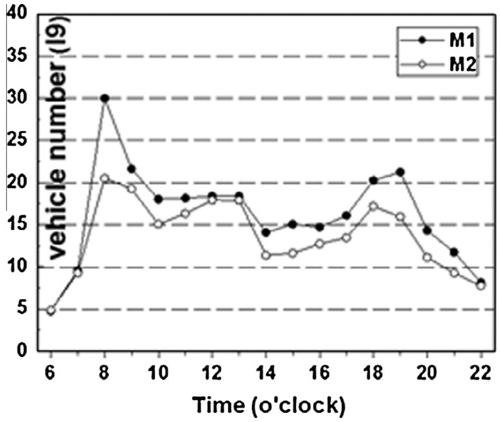

Fig. 9b. Average vehicle number of I9 under M1 and M2.

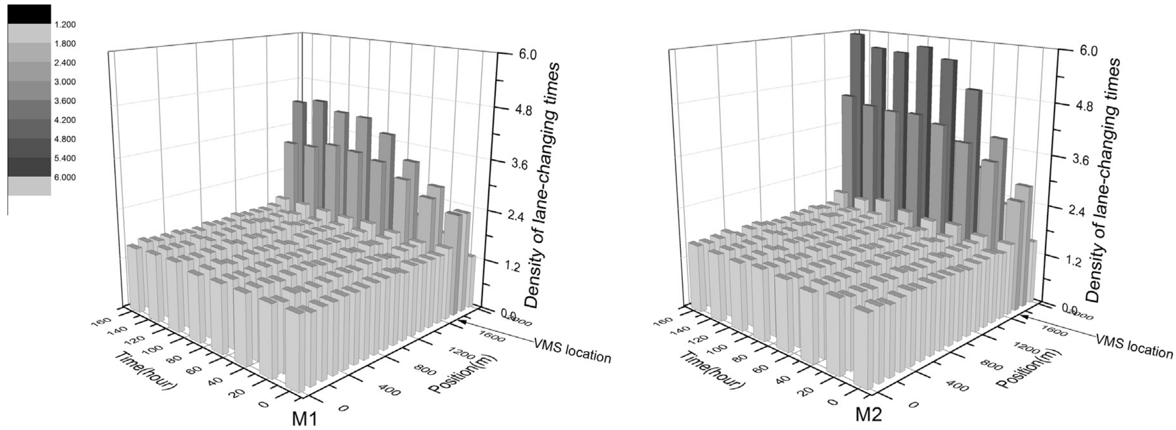

Fig. 10. Spatial–temporal-density diagrams of lane-changing times.

As shown in Fig. 10, once a driver enters within the sight of VMS, the density of lane-changing times begins to increase along the position direction, which indicates that guidance information has an obvious impact on drivers' route choice. As the simulation goes on, the density of lane-changing times within the sight of VMS increases gradually until it is stable along the time direction. It indicates that drivers learn from the repeated processes of passing the VMS, and the influence of VMS on drivers gradually increases. There are two differences between the spatial–temporal-density diagrams under M1 and M2: (1) Within the area influenced by VMS, the density of lane-changing times under M2 is larger than that under M1, which indicates that M2 has a greater influence on drivers. That is to say, drivers change their lanes to choose the optimal path with larger probabilities under M2 after seeing VMS information; (2) The time of density variation from low to high until stable under M1 is longer than that under M2, which shows that drivers take different time to adapt to VMS information under different information release modes. The mode, which has more stable guidance effect, is adapted more easily by drivers. Therefore, M2 has certain advantages in the stability of guidance effect.

In conclusion, the VMS information released based on M2 considers the vehicles that are about to run into the downstream roads from upstream roads, i.e., the congestion level at the time when the vehicle arrives at the downstream road is forecast and shown on the VMS, so the drivers' compliance rates are higher under M2. In addition, the goal of the guidance system, traffic equilibrium assignment is also reached. Therefore, M2 is the recommended mode for releasing guidance information based on the simulation conditions in this paper.

6. Conclusion

In this paper, SOAR has been adopted to describe the cognitive process of drivers' guidance compliance behavior. Through simulation experiments based on practical input, the properties of two guidance information release modes have been investigated with the detailed comparison of their guidance effect. This study lays the foundation for implementing traffic guidance information systems effectively, and provides guidelines in planning and designing guidance systems.

In principle, the rule for selecting guidance information release modes is not unique. It actually varies with many factors, such as the information released location, the flow characteristics and the composition of drivers. The method proposed here is one of the many methods available. With in-depth study and practical application of traffic guidance system, researchers will pay more attention to the study of traffic guidance compliance behaviors, and more methods will surely show up. Meanwhile, there are still many aspects to be considered to improve guidance effects, especially about management and technology aspects. Technical support, such as big data acquisition and processing [36,41,49], vehicle detection and tracking [16,23], and real-time video traffic transmission [25,32], short-term traffic flow forecasting [17,22], is the premise and foundation of traffic management. Based on the timely, accurate and comprehensive traffic information, traffic guidance measures, such as route guidance strategy, are put forward to influence drivers' compliance behaviors. The best guidance strategy should consider traffic conditions, drivers' characteristics and their reactions in different periods [33,35]. These are all the valuable research directions in the future.

Acknowledgments

The research described in this paper was substantially supported by Grants (50908155, 70971094, 71271150 and 71371134) from the National Natural Science Foundation of China, the Young Teachers Foundation Project (20090032120032) supported by the Doctorate in Higher Education Institutions of Ministry of Education, and the Program for Changjiang Scholars and Innovative Research Team in University (PCSIRT). Meanwhile, the authors appreciate the help and comments from editors and reviewers.

References

[1] J.L. Adler, Investigating the learning effects of route guidance and traffic advisories on route choice behavior, Trans. Res. Part C: Emerg. Technol. 9 (2001) 1–14.
[2] J.L. Adler, V.J. Blue, A cooperative multi-agent transportation management and route guidance system, Trans. Res. Part C: Emerg. Technol. 10 (2002) 433–454.
[3] J.L. Adler, W.W. Recker, M.G. McNally, A conflict model and interactive simulator (FASTCARS) for predicting enroute driver behavior in response to real-time traffic condition information, Transportation 20 (1993) 83–106.
[4] R.W. Allen, A.C. Stein, T.J. Rosenthal, D. Ziedman, J.F. Torres, A. Halati, A human factors simulation investigation of driver route diversion and alternate route selection using in-vehicle navigation systems, in: Vehicle Navigation and Information Systems Conference, 1991, pp. 9–26.
[5] M. Benakiva, A. Depalma, I. Kaysi, Dynamic network models and driver information systems, Trans. Res. Part A: Policy Pract. 25 (1991) 251–266.
[6] V.J. Blue, J.L. Adler, Cellular automata microsimulation for modeling bi-directional pedestrian walkways, Trans. Res. Part B: Methodol. 35 (2001) 293–312.
[7] P. Bonsall, I. Palmer, VMS signs – the importance of phrasing the message, in: Behavioral and Network Impacts of Driver Information Systems, John Wiley, London, 1998.
[8] P.W. Bonsall, M. Joint, Driver compliance with route guidance advice: the evidence and its implications, in: Vehicle Navigation and Information Systems Conference, 1991, pp. 47–59.
[9] J. Chen, P. Liu, W. Wang, Methods for en route parking guidance and information system survey in Nanjing, Urban Trans. China 6 (2006) 79–83.
[10] P.S.T. Chen, K.K. Srinivasan, H.S. Mahmassani, Effect of information quality on compliance behavior of commuters under real-time traffic information, Trans. Res. Rec.: J. Trans. Res. Board 1676 (1999) 53–60.
[11] W.H. Chen, P.P. Jovanis, Analysis of driver en-route guidance compliance and driver learning with ATIS using a travel simulation experiment, Institute of Transportation Studies, University of California, 1997.
[12] M. Cummings, Electronic sign strategies and their benefits, in: Proceedings of the7th International Conference on Road Traffic Monitoring and Control, 1994, pp. 141–144.
[13] F.P. Deflorio, Evaluation of a reactive dynamic route guidance strategy, Trans. Res. Part C: Emerg. Technol. 11 (2003) 375–388.
[14] F. Davidsson, N. Taylor, ITS Modelling in Sweden Using CONTRAM, TRL Ltd., Berkshire, United Kingdom, 2003.
[15] H. Dia, A conceptual framework for modelling dynamic driver behaviour using intelligent agents, in: Proceedings of the 6th International Conference on Applications of Advanced Technologies in Transportation Engineering, The National University of Singapore, Singapore, 2000, pp. 1–10.
[16] N.D. Doulamis, Coupled multi-object tracking and labeling for vehicle trajectory estimation and matching, Multimedia Tools Appl. 50 (2010) 173–198.
[17] L. Du, S. Peeta, Y.H. Kim, An adaptive information fusion model to predict the short-term link travel time distribution in dynamic traffic networks, Trans. Res. Part B: Methodol. 46 (2012) 235–252.
[18] A. Erke, F. Sagberg, R. Hagman, Effects of route guidance variable message signs (VMS) on driver behaviour, Trans. Res. Part F: Traffic Psychol. Behav. 10 (2007) 447–457.
[19] R. Fernández, Modelling public transport stops by microscopic simulation, Trans. Res. Part C: Emerg. Technol. 18 (2010) 856–868.
[20] W. Hua, B. Lin, A study on variable message sign to publish traffic flow guidance message, J. Trans. Syst. Eng. Inform. Technol. 4 (2006) 34–36.
[21] H.J. Huang, T.L. Liu, H. Yang, Modeling the evolutions of day-to-day route choice and year-to-year ATIS adoption with stochastic user equilibrium, J. Adv. Trans. 42 (2008) 111–127.
[22] S. Huang, A.W. Sadek, A novel forecasting approach inspired by human memory: the example of short-term traffic volume forecasting, Trans. Res. Part C: Emerg. Technol. 17 (2009) 510–525.
[23] A. Jazayeri, H. Cai, J.Y. Zheng, M. Tuceryan, Vehicle detection and tracking in car video based on motion model, IEEE Trans. Intell. Trans. Syst. 12 (2011) 583–595.
[24] R.M. Jones, J.E. Laird, P.E. Nielsen, K.J. Coulter, P. Kenny, F.V. Koss, Automated Intelligent Pilots for Combat Flight Simulation, in: Proceedings of the 15th National/10th Conference on Artificial Intelligence/Innovative Applications of Artificial Intelligence, Madison, WI, 1998.
[25] S. Kang, S. Lee, Y. Won, B. Seong, On-Line prediction of nonstationary variable-bit-rate video traffic, IEEE Trans. Signal Process. 58 (2010) 1219–1237.
[26] A. Khattak, J. Schofer, F. Koppelman, Commuters' enroute driversion and return decisions: IVHS design implications, in: Proceedings of International Conference on Travel Behavior, Quebec City, Quebec, Canada, 1991.
[27] H.N. Koutsopoulos, H. Xu, An information discounting routing strategy for advanced traveler information systems, Trans. Res. Part C: Emerg. Technol. 1 (1993) 249–264.
[28] C.J. Lai, Effects of color scheme and message lines of variable message signs on driver performance, Accident Anal. Prevent. 42 (2010) 1003–1008.
[29] C. Lai, K. Yen, Sedan drivers' attention and response to variable message signs on freeway in Taiwan, in: Proceedings of the 4th International Conference on Traffic and Transportation Psychology, 2004, pp. 8–12.
[30] J.E. Laird, A. Newell, P.S. Rosenbloom, SOAR: an architecture for general intelligence, Artif. Intell. 33 (1987) 1–64.
[31] J. Lee, K. Imai, Q. Zhu, Fluctuation-driven computing on number-conserving cellular automata, Inform. Sci. 187 (2012) 266–276.

[32] M.J. Lee, Video traffic prediction based on source information and preventive channel rate decision for RCBR, IEEE Trans. Broadcast. 52 (2006) 173–183.
[33] S. Lee, S. Shin, Variable message sign operating strategies: simple examples, Transportmetrica 7 (2011) 443–454.
[34] A. Lindkvist, A basis for evaluation – capacity, time consumption, and delay, Deliverable 23 of the TOSCA II project, Swedish National Roads Administration, Gothenburg, Sweden, 1995.
[35] J. Liu, R. Sun, L. Zhou, Study on guidance information expression based on drivers' compliance rate, in: First International Conference on Transportation Information and Safety, Wuhan, China, 2011, pp. 1730–1735.
[36] Z. Liu, S. Lin, K. Li, A. Dong, Traffic flow video detection system based on line scan CMOS sensor, Adv. Sci. Lett. 7 (2012) 478–483.
[37] C. Lu, Y. Tan, The simulation and analysis of urban transportation system complexity, Syst. Eng. 3 (2005) 4.
[38] R.P. Marinier, J.E. Laird, R.L. Lewis, A computational unification of cognitive behavior and emotion, Cogn. Syst. Res. 10 (2009) 48–69.
[39] K. Ozbay, B. Bartin, Estimation of economic impact of VMS route guidance using microsimulation, Econ. Impacts Intell. Trans. Syst.: Innovat. Case Stud. 8 (2004) 215.
[40] E. Ramsy, J. Luk, Route choice under two Australian travel information systems, ARRB Research Report ARR 312, 1997.
[41] D. Rosenbaum, J. Leitloff, F. Kurz, O. Meynberg, T. Reize, Real-time image processing for road traffic data extraction from aerial images, Technical Commission VII Symposium, 2010.
[42] P.S. Rosenbloom, J.E. Laird, A. Newell, Knowledge-level learning in SOAR, in: Proceedings of AAAT87, Morgan Kaufmann, Los Atlos, CA, 1987, pp. 499–504.
[43] J.C. Seck-Tuoh-Mora, G.J. Martínez, R. Alonso-Sanz, N. Hernández-Romero, Invertible behavior in elementary cellular automata with memory, Inform. Sci. 199 (2012) 125–132.
[44] R. Srinivasan, P.P. Jovanis, An evaluation of the attentional demand of selected visual route guidance systems, in: Vehicle Navigation and Information Systems Conference, Seattle, WA, USA, 1995, pp. 140–146.
[45] J. Swann, I. Routledge, J. Parker, S. Tarry, Results of practical applications of variable message signs (VMS): A64/Al accident reduction scheme and Forth Estuary Driver Information and Control System (FEDICS), in: Traffic Management and Road Safety, Proceedings of Seminar G held at the 23rd PTRC European Transport Forum, London, 1995, pp. 149–167.
[46] S. Tarry, A. Graham, The role of evaluation in ATT development: 4. Evaluation of ATT system, Traffic Eng. Control (1995) 688–693.
[47] P.V. Thakuriah, A. Sen, Quality of information given by advanced traveler information systems, Trans. Res. Part C: Emerg. Technol. 4 (1996) 249–266.
[48] J. Wahle, A.L.C. Bazzan, F. Klugl, M. Schreckenberg, Anticipatory traffic forecast using multi-agent techniques, Traffic and Granular Flow'99 (2000) 87–92.
[49] Z.J. Wang, Z.X. Li, L. Wang, The application of GPS data processing technique in map matching, In: 2011 International Conference on Transportation, Mechanical, and Electrical Engineering, Changchun, China, 2011, pp. 588–591.
[50] Y. Wang, M. Papageorgiou, G. Sarros, W.J. Knibbe, Real-time route guidance for large-scale express ring-roads, in: Intelligent Transportation Systems Conference 2006, pp. 224–229.
[51] K. Wochinger, D. Boehm-Davis, Navigational preference and driver acceptance of advanced traveler information systems, Ergonom. Safety Intell. Driver Interf. (1997) 345–362.
[52] H. Xu, J. Zhou, W. Xu, A decision-making rule for modeling travelers' route choice behavior based on cumulative prospect theory, Trans. Res. Part C: Emerg. Technol. 19 (2010) 218–228.
[53] M. Yikui, Y. Kefei, Analysis of the performance of the PGIS in metropolitan area, Road Traffic Safety 5 (2007) 33–36.
[54] Y. Yin, H. Yang, Simultaneous determination of the equilibrium market penetration and compliance rate of advanced traveler information systems, Trans. Res. Part A: Policy Pract. 37 (2003) 165–181.
[55] Y. Zhai, Z. Yi, P. Deng, On behavior of two-dimensional cellular automata with an exceptional rule, Inform. Sci. 179 (2009) 613–622.
[56] S. Zhong, S. Ma, G. He, Description and simulation of dynamic route guidance system road network, J. Syst. Eng. 24 (2009) 25–31.
[57] S. Zhong, L. Zhou, S. Ma, N. Jia, Effects of different factors on drivers' guidance compliance behaviors under road condition information shown on VMS, Trans. Res. Part A: Policy Pract. 46 (2012) 1490–1505.
[58] Y. Zhou, J. Wu, The research on drivers' route choice behavior in the presence of dynamic traffic information, in: Intelligent Transportation Systems Conference, Toronto, Canada, 2006, pp. 1304–1309.